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# **The use of disaggregated demand information to improve forecasts and stock allocation during sales promotions: A case study of small and medium suppliers**

## **Abstract**

**Purpose:** Our work highlights the importance of using disaggregated demand information at store level to improve sales forecasts and stock allocation during sales promotions.

**Design/methodology/approach:** Semi-structured interviews were combined with Monte Carlo simulation and optimisation modelling to estimate short-term promotional impacts. A case study of a major UK retailer and a sample of their suppliers was used to identify the benefits of using disaggregated demand data for improved forecasting and stock allocation.

**Findings:** The results suggest that there is a high degree of heterogeneity in demand at individual store level due to a number of factors including: the weather, the characteristics of shoppers, the characteristics of products and store format, all of which conspire to generate significant variation in promotional uplifts. Replenishment decisions that take (explicit) account of these factors are likely to result in greater net revenues from the retail promotion.

**Research limitations/implications:** This paper is based on a case study of one major UK supermarket and a small sample of suppliers. We believe the findings reflect barriers to 'best practice' that are widespread in the retail sector but the addition of more product categories can make the findings of this study more generalizable.

**Originality/value:** The paper is the first to a) use supermarket loyalty card data to generate store level promotional forecasts and b) quantify the benefits of disaggregating the allocation of promotional stock to the level of individual stores (rather than regional distribution centres).

**Keywords:** Sales promotions, demand forecasting, stock allocation, Monte Carlo simulation, optimisation.

**Paper type:** Research paper

## **1.Introduction**

It has been estimated that in 2012-13 over £14 billion of the £55 billion invested in price promotions in the fast moving consumer goods (FMCG) sector could have been retrieved by better co-ordination of supply and demand (IPM, 2015). There is growing evidence that in many cases, particularly for products supplied by small and medium-sized enterprises (SMEs), price promotions are implemented with limited understanding of the factors influencing demand and or supply (O'Dwyer et al., 2009; Parrot et al., 2010), resulting in missed opportunities for sales and the generation of avoidable promotional waste (IPM, 2015; Mena and Whitehead, 2008). This is particularly dangerous for SMEs who are often operating with tight margins and limited resources (Mirkovski et al., 2016; O'Cass and Sok, 2014; Felgate et al., 2012; Thakkar et al., 2008).

The promotional literature is inadequate in its treatment of this phenomena, relying on highly aggregated scanner data and assumptions about the promotional planning process that do not reflect industry practice, particularly for small-scale suppliers who lack the capacity or capability to adopt the principles associated with 'best practice.' This paper seeks to contribute to this area by illustrating the potential for improved demand and supply synchronization in retail supply chains, through the explicit use of disaggregated demand information (supermarket loyalty card data) for forecasting promotional uplifts and the allocation of promotional stock. The first section summarises the relevant streams of literature (marketing, operations management, information management) and identifies gaps in the evidence base. Part three discusses the research methodology and the results of the simulation and optimisation are presented in part four. The paper concludes with recommendations for business practice and further research.

## **2. Review of the promotions literature**

The promotions literature can be divided into two distinct areas. One is concerned with the demand-side and is focussed primarily on consumer reactions to different promotional stimuli. This is the domain of consumer behaviour and marketing research. The other is concerned with the supply-side factors and is focussed primarily on the replenishment cycle

and the how the supply chain responds to promotional activity. This is primarily the domain of operations management and operations research.

## **2.1 Marketing perspectives on promotions**

The marketing literature is concerned primarily with the way in which promotions are used as part of the marketing mix and how they affect consumer behaviour. Sales promotions result in brand switching (Miguel and Rao, 2009), purchase acceleration (Ailawadi et al., 2007) or category expansion (Liu-Thompkins and Tam, 2013).

Brand switching is defined as 'enticement of the consumer to purchase a different brand from its normal choice' (Blattberg and Neslin, 1990). However, it depends on the format (Pacheco and Rahman, 2015), type of consumer (Coulter and Roggeveen, 2014), and type of promoted product (Miguel and Rao, 2009). The majority of marketing studies acknowledge that this phenomenon occurs when products are promoted frequently and consumer loyalty to the brand is reduced, resulting in the switching of brands (Felgate et al., 2012). This behaviour is triggered when the promotional price is significantly lower than the reference price (Kim and Staelin, 1999).

Purchase acceleration is an important consequence of promotions that encourages consumers to buy promoted products in larger quantities or shorten the time between purchases (Aggarwal and Vaidyanathan, 2003; Kivetz et al., 2006). This induces consumer stockpiling which has consequences for both suppliers and retailers as it may result in a post-promotion dip (Ailawadi et al., 2007). Causes of purchase accelerations are complex and strongly dependent on consumer perceptions of sales promotions and situational factors, including shopping goals, shopper demographics and stock availability in stores (Kivetz et al., 2006; Kim and Staelin, 1999).

Promotions can increase the value of the whole product category or simply the value of the promoted brand within the category. The former is defined as category expansion whilst the latter is the result of brand switching (Haans and Gijsbrechts, 2011; Pacheco and Rahman,

2015). The ability of a promotion to increase purchase frequency is conditional upon the seasonality of product demand, competitive reactions to promotional activity, and the responsiveness of the supply chain (e.g. availability of inventory) (Quelch and Jocz, 2010; Liu-Thompkins and Tam, 2013). Category expansion of products seems to vary across different geographical markets and promotional instruments, which can be due to the heterogeneity of consumer demand, especially at store levels. This is important since stores are the places where actual purchases are made and any promotional planning without taking into account store level sales will result in inaccurate forecasts and execution.

## **2.2 Operations management perspectives on promotions**

An accurate estimate of consumer demand plays a key role in planning the logistical support for sales promotions, especially for production scheduling, inventory control, and delivery planning (Mantrala et al., 2009; Gligor and Holcomb, 2012). Sudden changes in customer demand during promotions act as a shock which creates stress in the supply chain. Linking demand data with upstream processes can help reduce the impact of variable demand (Taylor and Fearn, 2009). This integration of demand management with supply chain management is potentially important, particularly during the stock allocation and shelf replenishment stages of the promotional cycle (Gligor, 2014).

Distribution, replenishment, and operational integration during promotions can be achieved by linking inventory control with consumer demand (Gebennini et al., 2009; Gligor, 2014). This also helps in optimising resource allocation, which is particularly important for SMEs. However, this integration requires information visibility at store level which is a challenge, particularly for SMEs due to limited technological capabilities (Mirkovski et al., 2016; Thakkar et al., 2008). Due to the limitation of space and the increasing number of products on promotion, stock allocation is becoming a challenge for retailers, which is made all the more complicated by the heterogeneity of consumer demand and product attributes (e.g. perishability) (Gligor and Holcomb, 2012).

Promoted products are twice as likely to be out of stock as non-promoted products and shelf

replenishment at the store level and distribution centre has been identified as one of the two biggest reasons for stock-outs during promotions (Gruen et al., 2002; Felgate et al., 2012). This can be greatly reduced by better coordination through information sharing. If suppliers have better consumer information, they could help retailers in replenishment efforts, especially for distribution and store level management (Kembro and Selviaridis, 2015). Coordinated work of this kind is strongly dependent on the alignment of objectives of buyers and suppliers and the accuracy of demand forecasts. Detailed information about consumer demand at store level has the potential to reduce stock outs, as it gives both suppliers and retailers the visibility for making accurate and timely decisions about shelf space and stock allocation. A lack of collaboration in the supply chain results in less information sharing and an increase in inventory levels at every stage of the supply chain (Cho and lee, 2015).

### **2.3 The role of information sharing in the synchronization of demand and supply**

Up-to-date and relevant marketing information is needed at every stage of the supply chain. The most important information for demand and supply synchronization is the demand forecast (Kembro and Selviaridis, 2015). Improving forecast accuracy has been a key focus for collaborative efforts between retailers and suppliers in recent years. However, the focus has been too highly aggregated, at the level of the central warehouse or distribution centre (Pramatari and Miliotis, 2008), which takes inadequate account of the heterogeneity of demand and responsiveness to promotional activity at the store level (Pérez Mesa and Galdeano-Gómez, 2015).

As the heterogeneity of consumer demand increases so too should the amount of information required to forecast it (Kalchschmidt et al., 2006). Aggregating demand and applying a single model to forecast promotional sales for all stores leads to information loss and increased forecast error, which in turn affects inventory levels and reduces efficiency (Kembro and Selviaridis, 2015). This detailed analysis of both demand patterns and supply chain becomes even more important in a promotional environment, where clusters of consumers are affected by different environmental factors like weather, location, and store layout (Ailawadi et al., 2009).

Retailers are making increasing use of disaggregated sales data to segment their shoppers and design more targeted promotional events (Demoulin and Zidda, 2009). However, the use of this data for more accurate demand forecasting or process improvement upstream is limited (Evanschitzky et al., 2012; Kalchschmidt et al., 2006).

## **2.4 Gaps in the literature**

The analysis of the interplay between demand and supply has received little attention in the promotion literature to date. The literature highlights the importance of the relationship between demand and supply side factors and the use of information in the context of promotional planning and execution. However, where such studies have been undertaken, the context is invariably one involving retailers and large branded manufacturers, the majority of whom have formalised processes and resources available to deliver the kind of coordination and integration that is required in order for promotions to be successful. Such systems are unlikely to be found within small food producers and those producing own-label products, which account for a significant share of the products sold by supermarkets. Thus, there is a gap in the literature relating to the management of promotions when the products involved are supplied by SMEs.

The majority of empirical studies conducted thus far have used either a) scanner data, which is highly aggregated and therefore fails to capture the heterogeneity of demand within and between product categories and amongst different shopper segments, or b) survey data which relies on claimed/reported behaviour and is therefore highly unreliable. Thus, the second gap in the literature relates to the impact that the use of disaggregated sales data might have on the efficiency (reduced cost/waste) and effectiveness (sales uplifts) of price promotions.

Despite these gaps, the literature does highlight the important role that information plays in the decision-making process and the adverse consequences of inadequate consumer insight and inadequate sharing of information along the supply chain. This is critical for SMEs, as information sharing during important stages of promotional planning and execution could

help them utilise their resources more effectively, resulting in improved promotional performance. However, there is little evidence that disaggregated sales data is widely or routinely used by supermarkets or their suppliers, particularly for products supplied by SMEs, for whom management information is generally in short supply and/or used to a limited extent. Moreover, the bulk of the published research regarding the impact of price promotions is either focused on modelling consumer responses, using claimed behaviour or highly aggregated scanner data, or on stock allocation and replenishment processes that bear little resemblance to the way in which the majority of food SMEs operate. Thus, in seeking to capture both demand and supply side factors in greater detail, this research focuses specifically on the use of disaggregated sales data, broken down by store format and shopper segment, in order to generate accurate demand forecasts, optimise stock allocation at the individual store level and, as a result, improve promotional performance.

### **3. Research Methodology**

The fundamental hypothesis that this research seeks to test is that the use of disaggregated demand data has the potential to increase the effectiveness of price promotions for fast moving consumer goods.

Having identified significant gaps in the existing literature and a lack of research relating specifically to the management of promotions involving SMEs, it was deemed appropriate to conduct exploratory (qualitative) research before progressing with developing simulation and optimisation models for demand forecasting and stock allocation. Two product sectors were chosen with contrasting product characteristics: one representing branded, ambient products – cold pressed rapeseed oil – and one representing fresh, own-label products – root vegetables, mushrooms, and top fruit. The relevant personnel (marketing and or account managers) from a small number of suppliers from these categories were interviewed, either face-to-face or by telephone.

A semi-structured interview guide was used, based on key elements from the literature and focussed on the different stages of the promotional cycle. The primary purpose of the interviews was to establish the extent to which the approach to supermarket promotions,



adopted by these small-scale suppliers complied with the conceptual models and empirical evidence identified in the literature. In the first stage, rapeseed oil was selected as representative of the ambient product category and two small suppliers was contacted. They are subsequently identified as companies 'A' and 'B'. In the second stage, the account managers of four fresh produce companies representing three products (apples, mushrooms, and carrots) were selected to explore the practical process of sales promotions for fresh produce, from the setting of promotional objectives to evaluation and feedback. They are identified as companies 'C', 'D', and 'E'. These account managers were responsible for marketing, account management and the whole sales promotion process. Finally, a selection of retail buyers was interviewed to establish the retailer's perspective on the promotional process.

In order to explore the potential benefits of using disaggregated demand data, the simulation and optimisation incorporated three distinct levels of disaggregation: the characteristics of the shoppers, the characteristics of the stores and the level of customer penetration (Table 1).

***Insert Table 1 here***

The retailer involved in this study categorises its stores according to the profile of shoppers that patronise them, as up-market, mid-market, and price sensitive. Price sensitive shoppers are more likely to respond to promotions than up-market shoppers and this difference is captured by modelling demand from each of these categories. This classification is supported by Kucera (2014) who has shown that shopper behaviour during promotions is strongly impacted by socio-economic factors.

The second level of differentiation relates to store format, as the stock levels and replenishment cycles for larger (extra) stores will be very different from convenience (metro) formats. For this research, three different store sizes (extra, supermarket, metro) were used. This is supported by Andrews et al. (2011), who argue that the accuracy of consumer demand

models is improved when consumers are segmented into (homogenous) groups based on the type of store.

The third level of differentiation is the level of product demand, as measured by customer penetration. Stores in which demand for the product is higher (a higher proportion of shoppers purchase the product throughout the year) are likely to experience higher sales uplifts in response to any promotion relative to stores in which regular demand for the product is lower. This, in turn, will affect decisions relating to stock allocation at the start of the promotion and the rate of replenishment thereafter. By disaggregating demand data in this way, it is hypothesised that demand forecasts and stock allocation decisions will more effectively influence promotional uplift where it matters most – at the store level. Therefore, for each promoted product included in the simulation and optimisation modelling, twelve promotional scenarios were analysed.

In order to capture the potential effects of distinctly different product attributes, simulation modelling was conducted using data for two different categories of product (fresh and ambient) and two products from each category (carrots and mango, fresh; rapeseed and sunflower oil, ambient). The former were own-label, while the latter were branded products. The simulation model was implemented in Excel using @Risk add-on package. The structure of the resulting simulation model is shown in Figure 1.

***Insert Figure 1 here***

There are two types of input to the model: deterministic and stochastic inputs. Deterministic inputs used in the model were based on inputs from all stakeholders in the promotional cycle (suppliers, industry experts, retailers). These values represent important decision-making information like the type of product, the type of promotion, a delivery amount, sales price, lost sales penalty, and the perishability of stock. Stochastic values include weather and demand, which varies depending on weather (rainy or dry), store format (extra, supermarket, metro), customer type (upmarket, price sensitive), and customer penetration (high, low). Supermarket loyalty card data was to determine the level of customer penetration (the

percentage of customers buying the product at least once in the previous 52 weeks), as well as store level sales for the specific shopper segments.

In order to efficiently allocate stock during the promotional cycle, a mixed integer linear programming (MILP) model was developed using CPLEX 12.5 add-in for excel. The model, which takes the form of a multiple-choice knapsack problem, is parameterised using outputs from the simulation model. More formally let:

$J$  = the set of store format types, indexed by  $j$

$I$  = the set of stock delivery amounts, indexed by  $i$

$d_{ij}$  = the amount of stock associated with level  $i$  and store type  $j$

$v_{ij}$  = the (net) value of delivering stock level  $i$  to store type  $j$

$n_j$  = the number of stores of type  $j$  in the distribution network

$b$  = the total stock amount in the distribution centre

$x_{ij} = \begin{cases} 1 & \text{if stock level } i \text{ is delivered to store type } j \\ 0 & \text{otherwise} \end{cases}$

The problem can then be formulated mathematically as follows:

$$\max \sum_{j \in J} \sum_{i \in I} n_j v_{ij} x_{ij} \quad (1)$$

s.t.

$$\sum_{i \in I} x_{ij} = 1 \quad \text{for all } j \in J \quad (2)$$

$$\sum_{j \in J} \sum_{i \in I} n_i d_{ij} x_{ij} \leq b \quad (3)$$

$$x_{ij} \in \{0,1\} \quad \text{for all } j \in J, i \in I \quad (4)$$

The objective of the optimisation model (1) is to maximise total net revenue from all store types  $j$  in the distribution network. Constraints (2) ensure that only a single stock level  $i$  is delivered to each store type  $j$ . Inequality (3) requires that total stock deliveries are less than or equal to the amount of total stock level on hand  $b$  in the distribution network. Finally, constraints (4) require the stock delivery decision variables to take on binary variables.

For the purpose of this research, a total of four different parameterisations of the optimisation model were used based on differences in the type of product (fresh vs. ambient) and brand ownership (own label vs. brand label).

#### **4. Results**

In this section we first present the key findings from the stakeholder interviews, which informed the design of the simulation and optimisation processes, followed by the results from the simulation and optimisation modelling, in which we identify a) the significance of demand heterogeneity, at the different levels of disaggregation, and b) the potential for improved promotional performance, by comparing the actual (historical) sales with the outcomes from the simulation and optimisation.

From the sample verbatim (Table 2) it is clear that there are contrasting perspectives on the way in which retail promotions are planned and executed. Suppliers plan promotions taking into account previous sales volumes and retailers look at percentage volume uplifts but both this is generally done at a much higher level of aggregation than reported in the literature (Ramanathan and Muyldermans, 2011; Thomassey and Fiordaliso, 2006). This aggregation masks the significant variation that exists in the response of different shopper segments and for different types of store. In addition, there was little evidence of collaboration with promotional forecasts, although the suppliers recognised this as an area of weakness. This has been identified by researchers as a potential source of error and process improvement (Garretson et al, 2002)

The literature is divided on the range of forecast (in)accuracy, with some authors reporting it at 10 percent (Nagashima et al., 2015) and others claiming it to be nearer 30 percent (Mena

& whitehead, 2008). However, the interviews suggest that forecast error is a much bigger problem, at least for smaller branded product suppliers and suppliers of own label 'commodities'. This is particularly problematic for these suppliers, who typically lack the resources to accommodate promotional under-performance (missed sales and promotional waste).

***Insert Table 2 here***

It was also revealed during the interviews that promotional objectives and planning are done collectively not as two distinct stages of the promotional cycle, as presented in the literature (Anderson and Morrice, 2000; Croson and Donohue, 2006). In addition, the execution of promotional plans is dependent on the product category, the targeted market, the type of promotional mechanic applied, and the inventory management system at the store level (Thackeray et al. 2008; Zhang et al., 2008). The Interviews also supported our supposition that disaggregated demand data was not used at any stage of the promotional cycle.

Table 3 presents the significance levels involving comparison of historical sales broken into different levels of disaggregation. There are some interesting patterns observed in the levels of significance for different products and levels of disaggregation.

***Insert Table 3 here***

In the majority of cases, store format, customer type and penetration are important determinants of demand irrespective of a product category with the certain exceptions like carrots in smaller store format (metro). Similarly, customer type is generally significant for fresh but not in ambient products (olive oil & sunflower oil). Store format is significant regardless of product class, the exception being olive oil. Weather is important for some products (carrots and sunflower oil) but not for others (mango and olive oil).

After validating all inputs to the simulation model four different line graphs were plotted based on outputs of simulation model into optimization model to see the optimal net revenues. These optimal revenues were compared with the net revenues of stock allocation based on historical demands as currently practiced in figure 2. Comparison of all the four products (belonging to the ambient and fresh produce category) has shown that executing sales promotions (by taking into account the disaggregated consumer demand by customer type and store type) are better than executing promotions based on historical demand. Historical demand was calculated by previous sales history of product distributed to different store formats based on their store size ratio (i.e. extra is allocated 5 times more than metro).

***Insert Figure 2 here***

There are some interesting patterns within product categories. In the case of fresh produce category (carrot & mango) as the delivery amount increases the difference between the historical net revenue and optimal revenue decreases with varying degree. This trend is not observed in ambient category whereas delivery amount increases for olive oil, the difference between historical and optimal revenue first decreases and then it starts increasing at higher delivery amounts. Similarly, for initial increases in total stock, net revenue rises quickly but then tapers off as total stock becomes sufficiently large. For example, in carrot total net revenue increase from less than £50,000 to more than £300,000 when delivery amount changes from 37,000 units to 75,000 units. But it tapered off to £400,000 when delivery amount changes to 109,000 units till 127,160 units.

For the optimisation model, regardless of the total stock amount available, the optimised stock allocation results in higher net revenue than under the historical stock allocation. In some cases, in fact historical allocation results in losses (i.e. negative net revenue like mango & sunflower oil at 15,000 units). This validates the basic tenant of the research that higher level of disaggregation during the promotional cycle for stock allocation decisions do translate into greater benefits.

## 5. Discussion

Previous researchers have highlighted the importance of targeting distinct customer segments when designing promotional strategies (Hsu et al., 2012). The results of this study provide further evidence to support this view. For both product categories (fresh & ambient) the promotional impacts were significantly different for the different socio-economic segments (up-market and price sensitive) and the results for fresh carrots show that consumers who are more interested in the product (high product penetration) are much more likely to respond to promotions than consumers who have limited interest (low product penetration). These results are important in their own right, as they provide empirical evidence of the heterogeneity of consumer demand and promotional impacts across different consumer segments. In addition, they constitute a distinguishing feature of the simulation and optimisation models, enabling the modelling to reflect more accurately the dynamics of the promotional cycle as it happens, as opposed to what we assume (Raju et al., 1995). Using customer segmentations that are consistent with commercial practice facilitates more accurate forecasts of promotional uplifts at the store level and establish the scope for improvement based on disaggregated sales data that is available to the retail buyer and the supply base.

The weather was identified as an important factor influencing consumer behaviour, particularly during sales promotions for products with seasonal demand (Demirag, 2013). The importance of the weather was also highlighted in the executive interviews, yet the literature review revealed a lack of attention given to this factor in research focussed on short term (weekly/daily) sales uplifts associated with the promotional activity (Nikolopoulos and Fildes, 2013). Weather can have a significant impact on demand but that this is dependent on the product characteristics. These results are consistent with the findings of Srinivasan and Anderson (1998), who identified the limitations of assessing promotional impacts for highly aggregated product categories – carrots and mangoes are both from the fresh produce category but the impact of promotions and the moderating role of the weather are distinctly different.

One of the research questions addressed in this research is the extent to which promotional impacts vary according to the characteristics of the store, and in particular the size of the store, as reflected in the retail format (Extra, Super, Express). This is a gap in the literature highlighted by Bucklin and Gupta (1999), who advocated that use of store level data in promotional planning, to reflect the heterogeneity of store performance and shopping missions – family shopping missions in extra stores versus top-up shopping in convenience stores. The results of this study provide evidence of the need to account for different store characteristics when forecasting promotional uplifts (which impact stock levels and replenishment decisions), with significant differences in sales uplifts between the largest (extra) stores and the smallest (express) stores.

Comparison of all the four products (belonging to the ambient and fresh produce category) has shown that executing sales promotions (by taking into account the disaggregated consumer demand by customer type and store type) are better than executing promotions based on historical demand. Linking stock allocation with consumer purchasing behaviour at store level also validated Taylor and Fearn (2009) observation that linking upstream data with demand will improve revenues, inventory levels and reduces waste. It also shows that information sharing and order coordination can improve supply chain performance measured in better stock allocation (Eng, 2016). This improved performance directly impacts delivery plans and production scheduling as highlighted earlier in literature (Lummus et al., 2003; Kembro, and Selviaridis, 2015). Another important aspect of accurate stock allocation is better management of demand and capacity constraints of small food suppliers as highlighted by Eng (2016) and Zhao et al. (2002).

## **6. Conclusion**

This research clearly shows that sales promotions are a complex interplay of demand and supply side factors and use of highly disaggregated demand data at critical decision-making stages in the promotional cycle has the potential to improve the promotional effectiveness. It draws its strength from the scale and quality of consumer purchasing data and its use for simulating reality by practically understanding the process from the stakeholders and then



applying it to optimize the stock allocation decisions. Connecting demand and supply side through effective and relevant information sharing can change the way small business engage with their larger (and more powerful) retail customers. This can improve the balance of power between big retailers and give smaller suppliers an effective voice at key stages in the promotional cycle. The stakeholder interviews revealed that small suppliers make little or no use of information in the design of promotional strategies and little effort is made to evaluate the impact of promotions, beyond the aggregate increase in short-term sales. This research shows the importance of using information and the potential benefit thereof and provides evidence of the need to give small suppliers a voice in the decision-making process, to ensure that promotions are based on an objective assessment of consumer demand that is shared and understood by both suppliers and retailers. This will also make promotional activities more profitable and relationships more sustainable.

## **7. Limitations and future recommendations**

This research is based on the case study of UK biggest retailer and its suppliers whose promotional practices may not be followed by other big retailers and their small suppliers. There is a need to integrate different data sources, to improve the applicability of the model to the 'real world' context of daily adjustments to demand forecasts and stock replenishment decisions. The data requirements for the simulation and optimisation process are considerable and the generation of the necessary data is extremely time-consuming, given the permutations of product type, shopper type and store format. However, in order for the findings to be generalizable, further studies should seek to include a much broader (more product categories) and deeper (more products within each category) set of products.

This research has focussed exclusively on the short-term impacts of sales promotions, yet the literature acknowledges the need to take a longer-term view, to assess the impact of promotions on other variables – brand loyalty – and supply efficiency (primary production manufacturing and distribution). Future research should give consideration to these other variables and combine the benefits of richer insights of short-term demand impacts with broader insights of the longer term impact of promotions on other parts of the business/supply chain.

Promotional evaluation and feedback is a critical stage of the promotional cycle which improves the overall effectiveness by highlighting weakness and areas of improvement. Future research should try to incorporate this important step while designing sales promotions so that information sharing can be more effectively tracked and accurate consumer insights can be achieved. This will also improve the collaboration between retailers and suppliers as they will have a chance to sit together and analyse promotional cycle in more detail.

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Table 1. Three levels of disaggregated demand.

<b>Type of shoppers</b>	Upmarket			Price sensitive		
<b>Type of store format</b>	Extra	Supermarket	Metro	Extra	Supermarket	Metro
<b>Level of customer penetration</b>	High		Low		High	

Figure 1. The simulation model of product sales based on disaggregated demand.

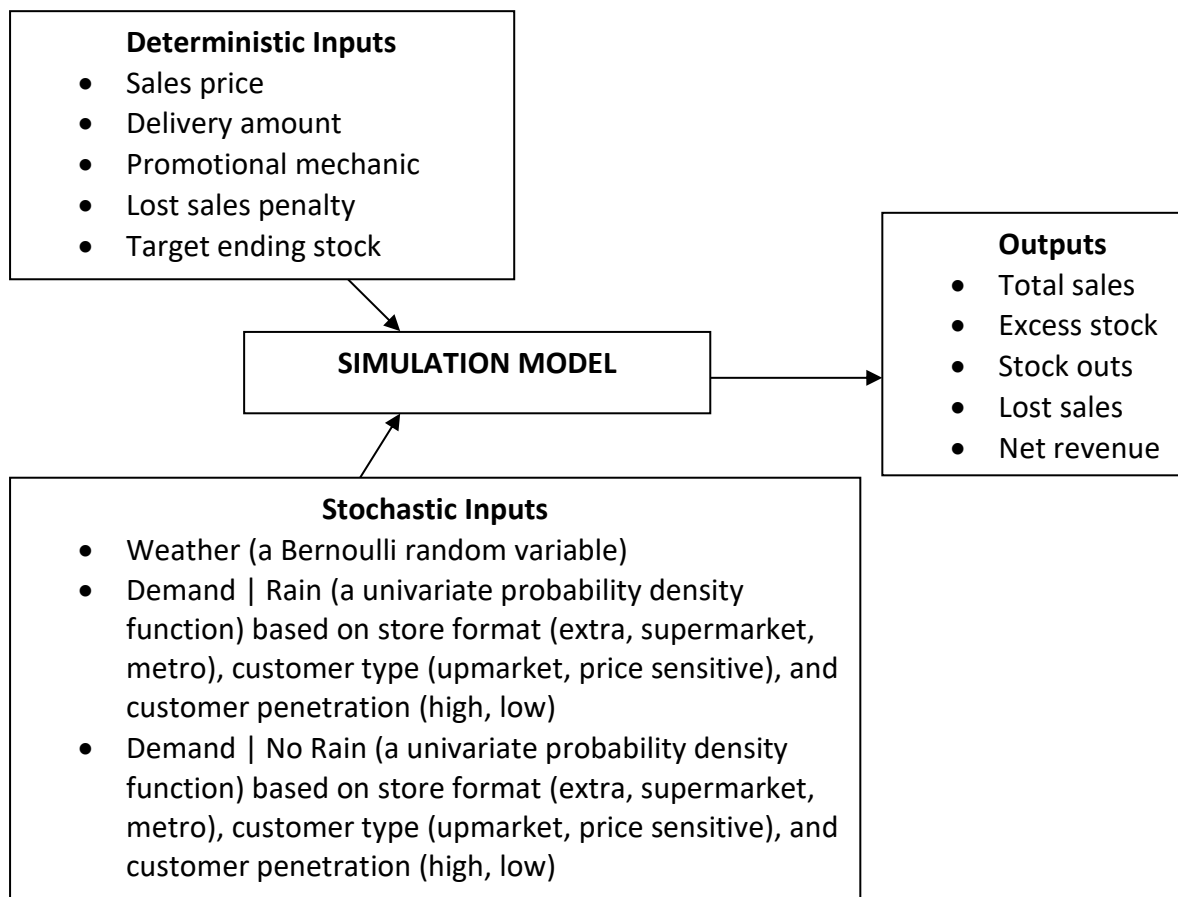




Table 2. Sample verbatim from the semi-structured interviews

Suppliers		Retailer
1. Promotional planning		
1.1 Promotional objectives		
Company 'C'	'You have your historical data, sales figure from the previous season and you have the data from the growers where they will tell you when they are ready to take the next crop'	'You and I negotiate that this promotion is coming up, so in terms of how much will be sold will depend on the uplift (two, three times or five). Theoretically, the buyer and supplier should agree what the uplift is going to be but there is no one way or set way of doing it"
Company 'B'	'There is an element of we know it works, we have done it before. Gut feeling/experience of what happens in previous different stores'	
1.2 Demand forecasting		
Company 'D'	'The weakest bit for us is the forecast, it (forecast error) varies between 50% and 100%'	'It's based on the store profile and customer types... we sometimes use our own experience to forecast the demand and ask for it from suppliers'
Company 'E'	'Historically the retailers forecasting is reasonably inaccurate. It (forecast error) is in the range of 50-100%.'	
2. Promotional execution		
2.1 Process of stock allocation		
Company 'A'	'Normally our orders are one or 2 pallets. (During promotions) it can increase from 6 to 8, so there can be time and space limitations'	'Products that have featured space like gondola ends or additional space will be better accommodated in terms of promotional stock. Its more about getting enough stock in the depot and moving it quickly enough to the stores'
Company 'E'	'It's the case of holding on and recalling enough loads from the fields and making sure you have enough packaging'	
2.2 Evaluation and feedback		
Company 'C'	'Only on an ad-hoc basis, the retailers will say look this promotion has worked. The sophistication with which we do this is not good. Yes, the promotion has worked but we don't know why or how '	'If we wanted a product and the forecast of the supplier was not good and we ran out in the middle (of a promotion) and had to get the supply from another supplier then next year the original supplier would not get the business'
Company 'A'	'I don't look at each promotion and say this one has done this and that one has done that. I should do but I don't'	

Table 3 Wilcoxon signed ranked test statistics (positive ranks) for different levels of demand disaggregation.

Product		Customer Type			Store Format			Customer Penetration			Weather		
		Upmarket vs. Price Sensitive			Extra vs. Supermarket	Supermarket vs. Metro	Metro vs. Extra	High vs. Low			Dry vs. Rainy		
		Extra	Super	Metro				Extra	Super	Metro	Extra	Super	Metro
Fresh	Carrot	-4.112**	-2.756*	-1.863	-6.996**	-4.711**	-4.762**	-4.206**	-3.894**	-4.373**	-1.886**	-3.715**	-3.479**
	Mango	-6.473**	-4.001**	-3.759**	-4.223**	-6.513**	-7.753**				-0.949	0.343	-0.789
Ambient	Sunflower Oil	-4.298	-2.500**	-2.500	-3.259**	-3.620**	-4.366**				-2.352	-3.402**	-5.084**
	Olive Oil	-1.949	-1.143		-1.949						-1.634	-0.389	

\* Significant at 5% level

\*\* Significant at 1% level

Figure 2: Comparison of total net revenue of optimized stock allocation of both fresh and ambient product categories based on disaggregated demand with stock allocation based on previous historical demand

